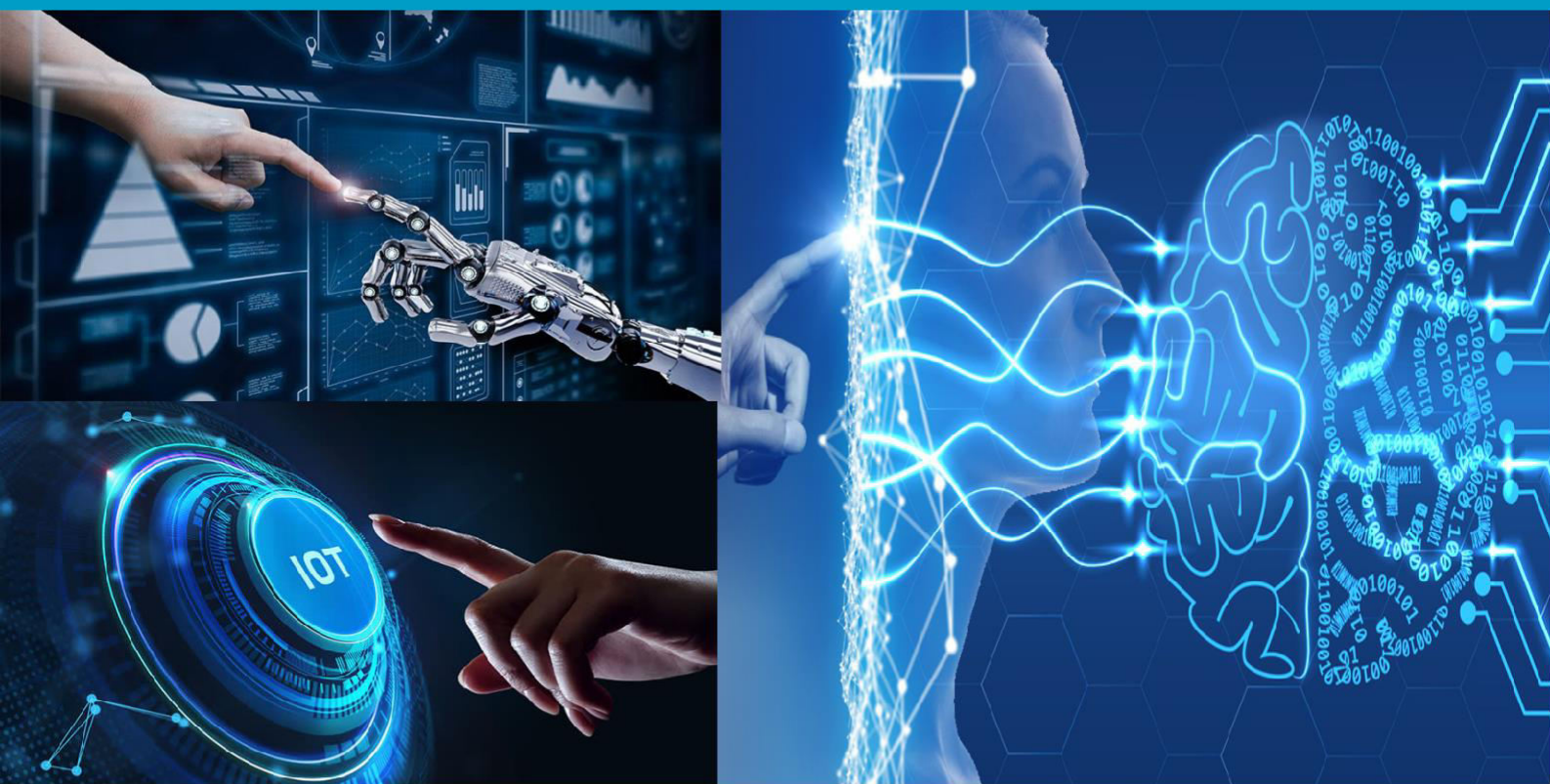




INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH

IN SCIENCE, ENGINEERING, TECHNOLOGY AND MANAGEMENT

Volume 9, Issue 7, July 2022



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.580



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An Analytical Survey on Dimension Reduction Based Face Recognition Systems

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ABSTRACT: Automatic Face Recognition (AFR), also known as biometric face recognition, is an appealing biometric technique because it focuses on the same identifier that humans use to separate one person from another: their "faces." Involving complex real system and how individuals represent faces in order to discern different identities with high accuracy is one of its key goals. In this article we have provided a study on dimension reduction-based face recognition systems.

KEYWORDS: Face Recognition, Dimension Reduction , PCA, LDA, DBN, LPP and SVD

I. INTRODUCTION

Control of the number of practical variables is necessary for any advancements in the optimal use of data processing and storage capacities. The decrease of the number of data-variables is a constant issue for researchers in fields as diverse as computer science, astronomy, bio-informatics, remote sensing, economics, and face recognition. The quantity of variables that are measured for each measurement is the basic dimension of the data. High-dimensional representations are produced, particularly when signals, processes, pictures, or physical fields are sampled. High-dimensional data sets bring both opportunities and challenges in mathematics and are certain to lead to new theoretical advancements [1]. Because these representations are frequently repetitive and the variables are associated, only a small portion of the initial representation space is ultimately supplied by the sample and the fundamental process. When taking into account particularly specific process classes, this is most likely the case. Dimension reduction techniques are required to enable low-dimensional depictions with little information loss.

The most important finding is that while face images can be thought of as points in a high-dimensional space, they frequently reside on a manifold (or lower-dimensional subspace) that is contained in the high-dimensional input images. A low-dimensional subspace of face appearance in a high-dimensional picture space needs to be appropriately defined and determined. The inherent dimensionality of the manifold and the extraction of its main directions have been studied extensively utilising dimensionality reduction methods based on linear transformations. Data reduction using dimensionality reduction is an effective strategy. Dimension reduction, which in statistics means the practice of limiting the number of random variables taken into account, can be further broken down into feature selection (fig. 1) and feature extraction. The objective is to identify a low-dimensional description of the data that accurately describes the data in both scenarios. A subset of all the features is selected using feature selection, and additional features are extracted using feature extraction from already existing features.

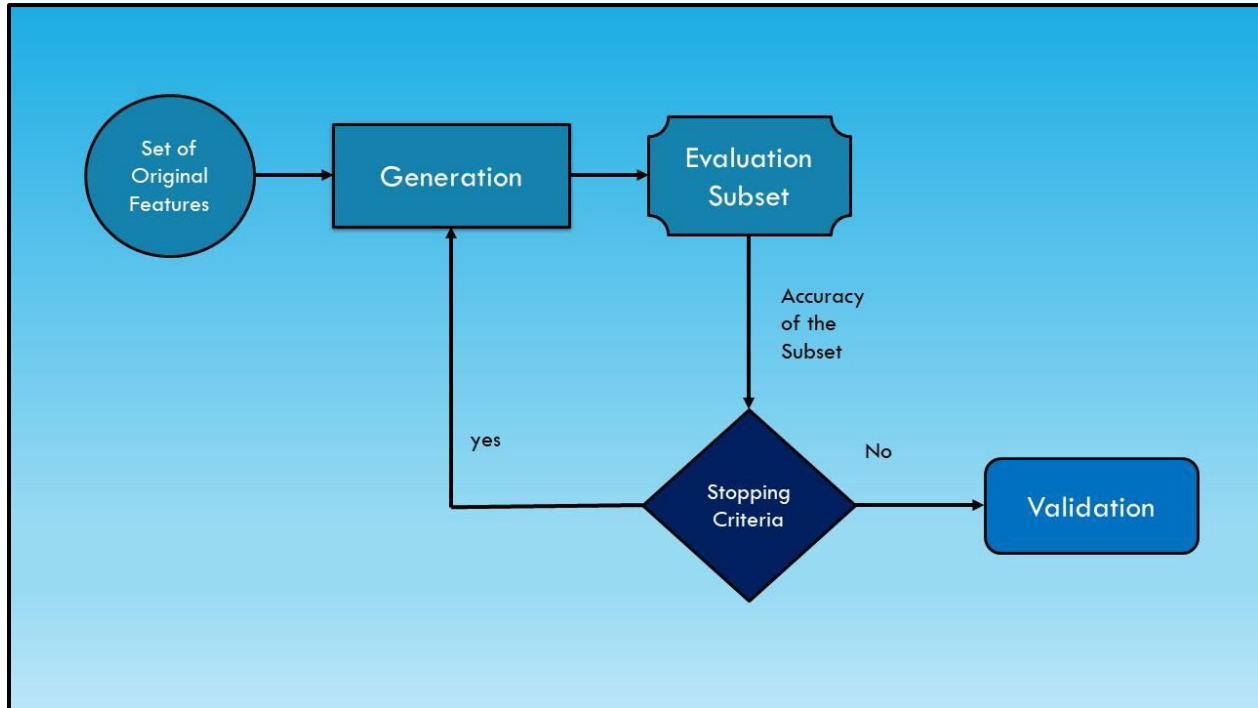


Fig 1: Process of Feature Selection

II. RELATED WORK

Face recognition uses a database of recognised faces to identify a face in a picture or video. True, faces must be entered into the system in order to compile a list of unique facial characteristics [2-3]. The system then breaks down a new image into its constituent parts and compares them to the data stored in the repository. Features analysis is used to categorise emotions [4–5]. A lot of work has also been done in the area of picture enhancement, including methods for image inpainting [6], counting the number of individuals in an image [7], image smoothing [8], and recovering an original image from a ruined image [9-10].

High computational and storage demands result from working with high-dimensional datasets. Utilizing feature extraction techniques could help decrease this storage requirement and speed up computations. Previous studies have shown that dimensionality reduction is an effective technique to identify data intrinsic structures and to extract a smaller number of variables that encapsulate the high-dimensional data's most important characteristics. The dimension of face image vectors has been reduced over the past few decades using a variety of linear and nonlinear dimension reduction techniques, including principal component analysis (PCA) and its nonlinear variants (KPCA) [11-12], local linear embedding (LLE), and curvilinear component analysis (CCA).

III. DIMENSION REDUCTION BASED FACE RECOGNITION METHODS:

Fig 2 provides a basic flow of face recognition using Dimension reduction.

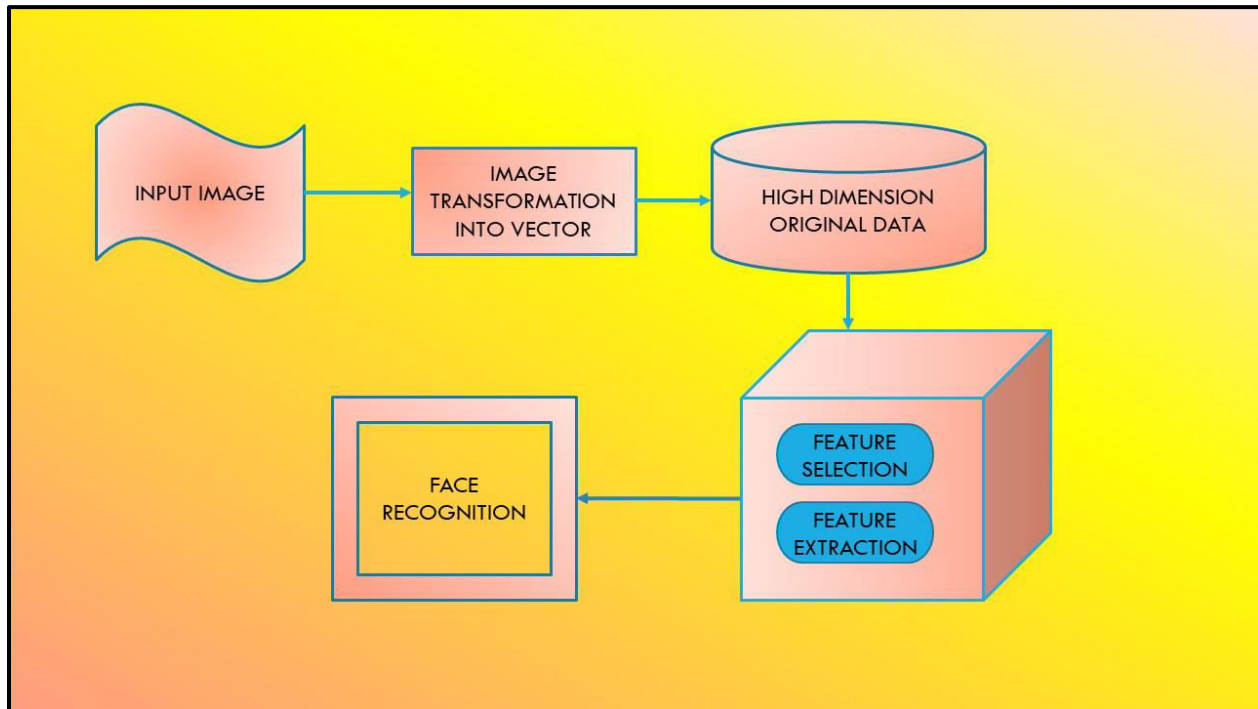


Fig 2: Basic Flow of Dimension Reduction Based Face Recognition

There are many approaches for overcoming the dimensionality problem, some of which are linear and others nonlinear. Common linear approaches include PCA, LDA, and LPP, and nonlinear methods include ISOMAP & Eigenmaps. The two most popular subspace learning methods for face recognition are PCA and LDA. With these techniques, the faces from the training sample are projected into a low-dimensional representation space where recognition is performed. The primary assumption underlying this method is that face recognition can be done in a smaller space—the face space, which is determined by the feature vectors—than the image space, which is determined by the number of pixels in the images.

PRINCIPAL COMPONENT ANALYSIS (PCA)

The benefit of PCA is that it can capture global information while ignoring localised features[3]. Fisher faces from LDA approach is proven to perform better for huge data sets and extracts distinguishing elements between classes. The Small Sample Space (SSS) problem is one of its flaws. By resolving a variational problem that best preserves the neighborhood structure of the data set, linear projective maps, or LPPs, are created. The benefit of PCA is that it can capture global information while ignoring localised features. Face pictures can frequently be seen as dots drawn on a low-dimensional manifold that is concealed in a high-dimensional environment. In particular, we can imagine a rubber sheet bent into a (high-dimensional) ball. An unfolding of the sheet and the explicit presentation of its low-dimensional form are the goals of a dimensionality-reducing mapping. The mapping preserves topology if the sheet is not torn in the process. Additionally, the mapping maintains the metric structure of the original space if the rubber



is not extended or contracted. PCA generates a concise representation and is certain to identify the manifold's dimensions.

LINEAR DISCRIMINANT ANALYSIS

Fisher faces from LDA approach is proven to perform superior for huge data sets and extract distinguishing features between classes [13]. The Small Sample Space (SSS) problem is one of its flaws. By resolving a variational problem that best preserves the neighbourhood layout of the data set, linear projective maps (LPPs) are created. LDA is a supervised learning algorithm. While requiring that data points from the same class be close to one another, LDA looks for project axes on which the data points from different classes are distant from one another. LDA encodes discriminating information in a linear separable space using bases that are not always orthogonal, in contrast to PCA, which encodes information in an orthogonal linear space. In general, LDA-based algorithms are thought to be better than PCA-based ones. However

SINGULAR VALUE DECOMPOSITION (SVD)

With various uses in signal processing and statistics, singular value decomposition (SVD) is a significant factorization of a rectangular real or complex matrix [14]. This method is used to extract the overall, global features from the training set for face recognition, and SVD is the best. By identifying a few orthogonal linear combinations of the initial variables with the highest variance, SVD aims to minimise the dimension of the data. The fundamental principle of SVD is the reduction of a high dimensional, highly variable set of data points to a lower dimensional space that more vividly reveals the substructure of the source data and sorts it from greatest variance to greatest uniformity. Because one may easily discard variation below a specific threshold to drastically decrease the data while still being certain that the key correlations of interest have been preserved, SVD is useful for pattern recognition applications. Three perspectives that are consistent with one another can be used to examine singular value decomposition (SVD). One way to look at it is as a technique for turning a set of correlated variables into a set of uncorrelated ones that better highlight the numerous connections between the source data points. SVD is a technique for figuring out and ranking the dimensions along which data points show the most variability. This relates to the third method of looking at SVD, which holds that once we've determined where the most variance is, we can obtain the closest approximation to the original data points with less dimensions. SVD can therefore be thought of as a data reduction technique.

LOCALITY PRESERVING PROJECTIONS (LPP)

In addition to obtaining a face subspace that best identifies the fundamental face manifold structure, LPP discovers an embedding that maintains local information. The Laplacian faces are the most accurate linear approximations to the eigenfunctions of the face manifold's Laplace Beltrami operator. By doing this, the unwelcome variances brought on by modifications in the lighting, stance, and facial expression may be avoided or minimized [15]. By doing this, the unwelcome variances brought on by modifications in the lighting, stance, and face expression may be avoided or minimised. Theoretical investigation demonstrates that alternative graph models can be used to derive PCA, LDA, and LPP. The facial images are mapped onto a face subspace using LPP for analysis. LPP has many of the same characteristics for data description as nonlinear methods like Laplacian Eigen maps or locally linear embedding. However, LPP is linear and, more importantly, it is defined across the entire ambient space, not simply on the basis of the training data points. It creates a graph using the data set's neighbourhood information. A transformation matrix that transfers the data points to a subspace is generated using the concept of the graph's Laplacian. In a particular sense, the knowledge about the immediate neighbourhood is best preserved by this linear transformation.



A continuous map that simply results from the topology of the manifold can be thought of as a linear discrete approximation to the representational map produced by the procedure. The issue of creating low-dimensional depictions via kernel-based approaches for face recognition has generated some focus in the interim.

DEEP BELIEF NETWORK (DBN)

Another popular unsupervised deep learning technique to minimise the dimension of the feature vectors and extract features from high-dimensional data is the deep belief network (DBN) [16]. A deep belief network is a generative probabilistic model. In contrast to the discriminating model, which only assesses either Label or observation, the generation model builds a joint distribution between observational data and labeling and assesses both observation and labels. In order to more effectively search for products whose image contents match and increase query accuracy, the resemblance between the photographs is learned in accordance with the data of the product class.

DEEP LEARNING METHODS

In the age of big data, a more potent and intricate deep learning model may better recover the structure of the characterisation data and more effectively and accurately record the properties of vast data, allowing for precise predications. The goal of the deep learning approach is to uncover the true relationships between variables and the fundamental pattern of the data.

IV. CONCLUSION

Although some existing approaches can tackle the facial recognition problem rather successfully in certain situations, there are still a number of difficulties with the task in general. Several face recognition methods have been put forth in recent years. The new methods include managing low quality photos, recognising facial expressions from faces, recognising faces from three-dimensional scans, recognising faces from still images, recognising faces from video clips, etc. The majority of techniques require high dimensional data, which increases the need for computing and storage. In order to prepare data for representation and categorization, dimension reduction has thus become essential. Basically, PCA and LDA only detect the Euclidean structure. If the face images are on a nonlinear submanifold that is buried in the image space, they are unable to find the underlying structure. The nonlinear nature of the manifold has been discovered using some nonlinear methods, such as Isomap, LLE, and Laplacian Eigenmap. Despite being unsupervised, LPP appears to have discriminatory power. The nonlinear multimodal topology of the face space should be able to be found using an effective subspace learning method for face identification.

REFERENCES

- [1] Donoho, D.L. (2000) High-Dimensional Data Analysis: The Curses and Blessings of Dimensionality. Lecture Delivered at the "Mathematical Challenges of the 21st Century" Conference of the American Math. Society, Los Angeles.
- [2] Sanju, Kirti Bhatia, Rohini Sharma, An analytical survey on face recognition systems, International Journal of Industrial Electronics and Electrical Engineering, Volume-6, Issue-3, Mar.-2018, pp. 61-68.
- [3] Sanju, K. Bhatia, Rohini Sharma, Pca and Eigen Face Based Face Recognition Method, Journal of Emerging Technologies and Innovative Research, June 2018, Volume 5, Issue 6, pp. 491-496.
- [4] Ankit Jain, Kirti Bhatia, Rohini Sharma, Shalini Bhadola, An Overview on Facial Expression Perception Mechanisms, SSRG International Journal of Computer Science and Engineering, Volume 6 Issue 4 - April 2019, pp. 19-24.



- [5] Ankit Jain, Kirti Bhatia, Rohini Sharma, Shalini Bhadola, An emotion recognition framework through local binary patterns, Journal of Emerging Technologies and Innovative Research, Vol -6, Issue-5, May 2019.
- [6] Jyoti, Kirti Bhatia, Shalini Bhadola, Rohini Sharma, An Analysis of Facsimile Demosaicing Procedures, International journal of Innovative Research in computer and communication engineering, Vol-08, Issue-07, July 2020.
- [7] Deepak Dahiya, Kirti Bhatia, Rohini Sharma, Shalini Bhadola, A Deep Overview on Image Denoising Approaches, International Journal of Innovative Research in Computer and Communication Engineering, Volume 9, Issue 7, July 2021.
- [8] Nakul Nalwa, Shalini Bhadola, Kirti Bhatia, Rohini Sharma, A Detailed Study on People Tracking Methodologies in Different Scenarios, International Journal of Innovative Research in Computer and Communication Engineering, Volume 10, Issue 6, June 2022.
- [9] Mahesh Kumar Attri, Kirti Bhatia, Shalini Bhadola, Rohini Sharma, An Image Sharpening and Smoothing Approaches Analysis, International Journal of Innovative Research in Computer and Communication Engineering, Volume 10, Issue 6, June 2022, pp 5573-5580.
- [10] Yogita, Shalini Bhadola, Kirti Bhatia, Rohini Sharma, A Deep Overview of Image Inpainting Approaches, International Journal of Innovative Research in Science, Engineering and Technology, Volume 11, Issue 6, June 2022, pp. 8744-8749.
- [11] Huang, W. and Yin, H. (2009), 'Linear and Nonlinear Dimensionality Reduction for Face Recognition' 16th IEEE International Conference on Image Processing (ICIP), pp. 3337–3340.
- [12] Huang, W. and Yin, H. (2012), 'On Nonlinear Dimensionality Reduction for Face Recognition', Image and Vision Computing, vol. 30, no. 45, pp. 355–366.
- [13] <https://www.javatpoint.com/linear-discriminant-analysis-in-machine-learning>
- [14] Zeng, G. (2007). Facial Recognition with Singular Value Decomposition. In: Elleithy, K. (eds) Advances and Innovations in Systems, Computing Sciences and Software Engineering. Springer, Dordrecht, pp 145-148.
- [15] Fadi Dornaika and Ammar Assoum, Selective Locality Preserving Projections for Face Recognition, Proceedings of SPIE - The International Society for Optical Engineering, 2011.
- [16] Hinton GE (2009) Deep belief networks. Scholarpedia 4(5):5947.



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